SICASE-0002
Forecasting Multivariate Time Series Meteorological Data for Solar Thermal Cogeneration Systems

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Abstract

The high usage of fossil fuel to produce energy for the increasing demand of energy has been the primary culprit behind global warming. Alternative energy supply is thus necessary in order to prevent the situation from worsening. Recently, renewable energies such as solar energy has emerged as potential alternative energy resources due to its abundance all over the globe Solar energy can be harnessed using available system such as solar thermal cogeneration systems. However, fluctuations of solar radiation is one of the main challenge faced by the implementation of solar thermal cogeneration system due to its high variability. In order to have solar thermal cogeneration systems function smoothly and continuously, knowledge on solar radiation's intensity several minutes in advance are required. While there exist various solar radiation forecast models, most of the proposed model are time consuming. In this research, a new methodology to forecast solar radiation via several meteorological data that incorporates dimension reduction technique is proposed. Based on the proposed methodology, two prediction models, Artificial Neural Network and statistical are established.

Keywords: Solar radiation, forecast, artificial neural network, time series

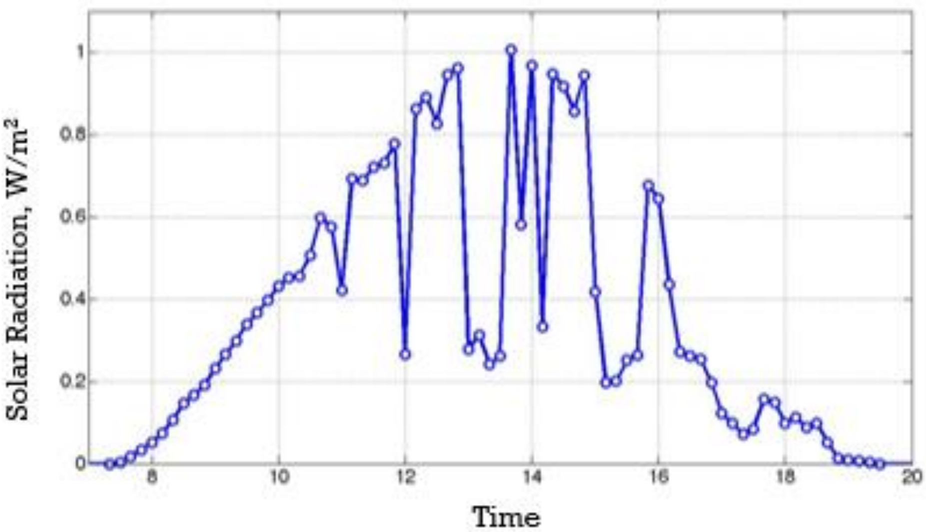
1. Introduction

Global warming is a top environmental issue concerned by most of the people in recent. It brought effects not only to the environments but to human as well. Among the victims, human population are affected the most. Looking on the negative impacts brought by global warming to human and environments, reducing the demand on fossil fuel is deemed necessary. Indeed, there is no single solution of stopping people from using it. However, switching the demand from fossil fuel to other renewable energy such as solar, wind and marine energy is one of the consensuses from the scientists.

Renewable energy is generally characterized as clean and durable energy. There are many forms of renewable energy, and most of these energies are inter-related to sunlight. For instances, solar thermal system harnesses solar energy to generate electrical energy while hydroelectricity generator generates hydropower via ocean's movement. Since there are much renewable energies have been found in nowadays, some researches had been done to compare among these found renewable energies. Most of the scientists believed that solar energy could be one of the future potential powering source in the world.

Located near the equator, Malaysia receives abundant solar radiation annually, which indirectly caused to dramatically increment of solar energy usage in the past decade. However, power fluctuations is one of the many challenges faced by the implementation of solar energy. This is because of the intermittency and variability of solar radiation (see Figure 1) received in Malaysia. To overcome such obstacle, establishment of an accurate solar radiation prediction model is important.

Figure 1. Measured solar radiation during daytime

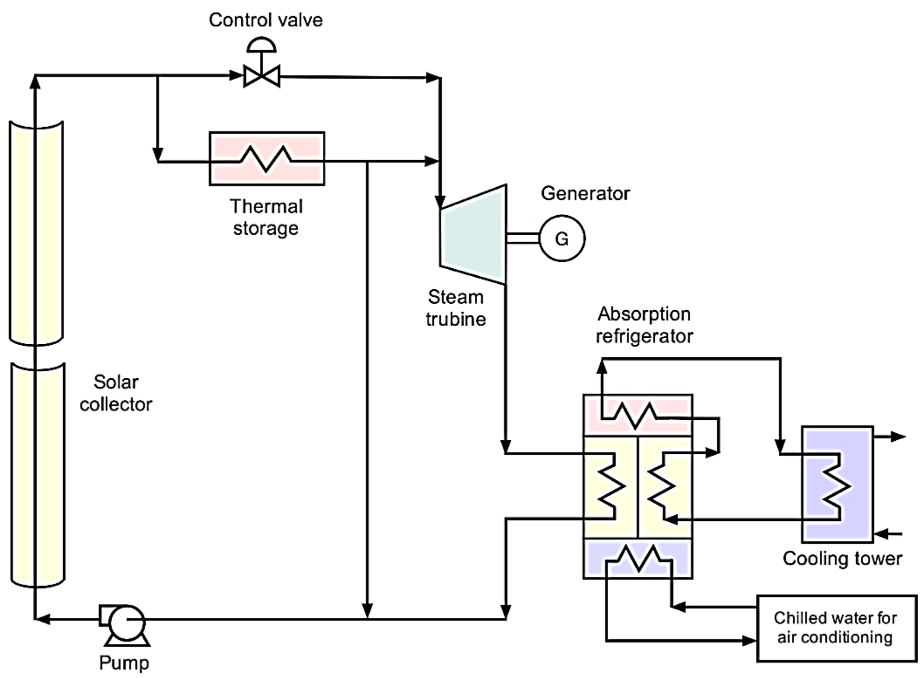


2. Literature Review

Solar energy can be harvested and transformed into useable electricity through photovoltaic conversion and solar thermal power cogeneration system. Photovoltaic conversion (PV), works in such a way that electricity is created directly from the sun via the solar panels. PV are composed mainly of silicon and other semiconductor materials which helps to store extra-generated energy when solar radiation is found abundant [1].

On the other hand, solar thermal cogeneration system (STCS) is a complete energy system, converting radiant energy into a useable energy form, providing both electrical and thermal energy for a detached residential or commercial structure. Here, solar thermal describes converting the sun's radiation into usable heat energy and cogeneration describes generating electricity while using excess heat for thermal needs. STCS employs a Rankine cycle heat engine with a closed-loop water-steam boiler [2]. Basic components of STSC include a solar collector, working fluid, thermal storage, turbine, and generator as shown in Figure 2.

Figure 2. Schematic diagram of solar thermal cogeneration system



The collector in STCS consists of a long rectangular curved mirror (concentrator) and a central heat pipe (receiver) located at the focal line of the curved mirror. The sunlight which enters the curved mirror is parallel to its plane of symmetry and will then focus along the focal line, where working fluid within the pipe is intended to be heated [2]. A tracking mechanism maintains concentrator focus as the sun traverses the sky is used to efficient heating up the working fluid within a pipe. The working fluid plays an important role to drive STCS's performance under changeable solar radiation. One of the common used working fluid is water. This is because water can easily be boiled and converted into steam phase within a short period [2].

Another main components that are incorporated in STCS is thermal storage. It behaves as a

container to store thermal energy (steam) in molten salt for later use. Thermal storage is controlled by a valve which manipulates the in-and-out of steam flow [2].
Generally, any thermal storage that can be found in nowadays have three main functions:

i.	Charge	:	A heat source is used to provide heat to the storage medium
ii.	Store	:	The storage medium is used to store the heat for later use
iii.	Discharge	:	The heat leaves the storage medium in a controlled manner to be used for another purpose

The three main functions mentioned in above are switched among each other. This switching processes depend on the solar radiation that will be collected in a day by STCS. For instances, the thermal storage will switch from discharging mode to charging mode when the demand of electricity is higher than the solar radiation received and vice versa.

Unfortunately, STCS needs a great improvements on its thermal storage. This thermal storage tends to switch frequently from charging to discharging or vice versa under variability of solar radiation. During mode switching, the thermal storage also takes time to stabilize the steam pressure within the storage. In general, STCS needs couples of minutes to the whole system respond. Hence, to ensure thermal storage in STCS is able to perform efficiently, an accurate short-term solar radiation forecasting several minutes in advance is needed.

Today, numerous numbers of methodologies to forecast solar radiation has been proposed by the researchers around the world. The common methodologies found on solar radiation prediction are based on sky image or by meteorological data.

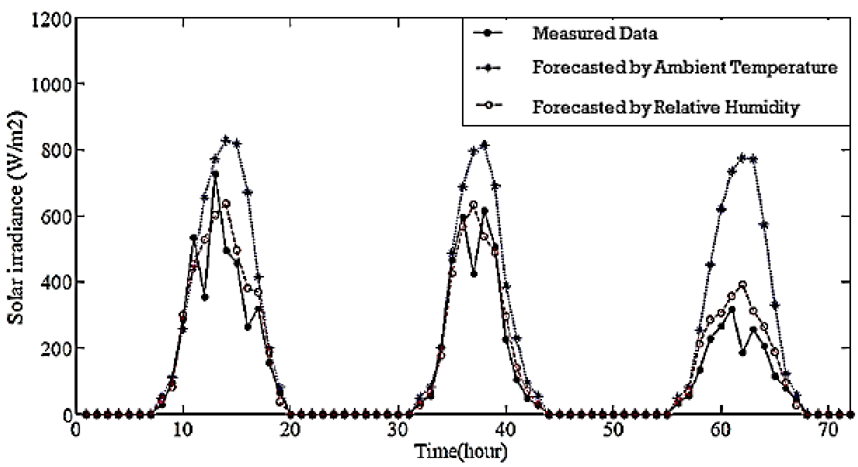
Solar radiation prediction based on sky image detects cloud movements to estimate future cloud position over solar panels. Subsequently, these information are used to determine solar radiation fluctuations incurred by cloud. A number of researches that utilizes sky images can be found from the literature, for instances, see [3], and [4]. Although this approach of predicting solar radiation gives a good prediction results, it has disadvantages. One of it is computational time. This is due to the method itself which uses image with thousands of pixels to extract the information. In addition, the sky images are captured under the sun. The glaring effect that is caused by sunlight can result to the resolution of the captured images to be severely reduced. Thus, distracting the information that can be extracted from the captured images.

Another popular approach in forecasting solar radiation is based on past observed meteorological data. Many substantial researches have been done through this methodology. For instances, Taylor et al. (2003) and Ghanbarzadeh et al. (2009) forecasted solar radiation based on meteorological data [5, 6]. There are numerous variables have been grouped as meteorological data such as sunshine duration, relative humidity, mean air temperature and other variables.

Today, many significant researches have been conducted on artificial neural network (ANN) such as solar energy forecasting. For instances, Tymvios et al. (2005) used mean sunshine duration and mean temperature as inputs to train ANN model to estimate the solar radiation on a

horizontal surface [7]. On the other hand, Rehman et al. (2008) employed daily and yearly maximum air temperature, daily mean air temperature, relative humidity to estimate the global solar radiation in Saudi Arabia [8].
Although many meteorological data can be found, unfortunately, most of the methodologies uses only single variable to forecast solar radiation. For instances, Taylor et al. (2003) used ambient temperature and relative humidity independently to forecast solar radiation. The obtained results are plotted together with measured solar radiation for comparison as shown in Figure 3 [5]. In Figure 3 below, it is clearly highlighted that the predicted results via single variable do not actually satisfy much to the measured solar radiation data.

Figure 3. Solar radiation predictions with different meteorological variables (ambient temperature and relative humidity) [5]



On the other hand, Mubiru et al. (2008) had developed another forecasting model with satisfactory prediction accuracy by using numerous meteorological variables [9]. The involved parameters are maximum temperature, sunshine duration and cloud cover. This shows that accounting other meteorological factors improves the accuracy of solar radiation prediction.
While accounting more variables can improves the prediction accuracy, it often tend to complicate the data structure and leads to a longer computational time. Thus, in this study as well, a multivariable solar radiation forecasting model that incorporates dimension reduction technique are developed to predict solar radiation more accurately at a lower computational time,

The main objectives of this project are:

- To determine dominant meteorological factors affecting solar radiation
- To develop solar radiation forecast methodology based on principal component analysis
- To establish an Artificial Neural Network (ANN) and statistical forecast model on the developed methodology
- To compare the accuracy of developed ANN model with statistical forecast model

3. Methodology

Several types of meteorological data are collected. They are relative humidity, wind speed, air temperature, wind gust, and wind. These data were collected from October 2015 to November 2015 from the rooftop of MJIIT building in UTM KL.

Then, Principal Component Analysis (PCA) were implemented on these data to identify the principal components and reduce the dimension of the data set. This is done by first computing the covariance and correlation between every pair of variables using Equation (1) and (2) respectively.

$$\mathrm{cov}(x,y)=\frac{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)\left(y_i-\bar{y}\right)}{n-1} \tag{1}$$

$$r_{(x,y)}=\frac{\mathrm{cov}(x,y)}{s_x s_y} \tag{2}$$

Then, the eigenvector and eigenvalue of the matrix are computed using the determinant (equation (3)) of it characteristic polynomial (equation (4)).

$$(A-\lambda I)V=0 \tag{3}$$

$$p(\lambda)=\left|A-\lambda I\right| \tag{4}$$

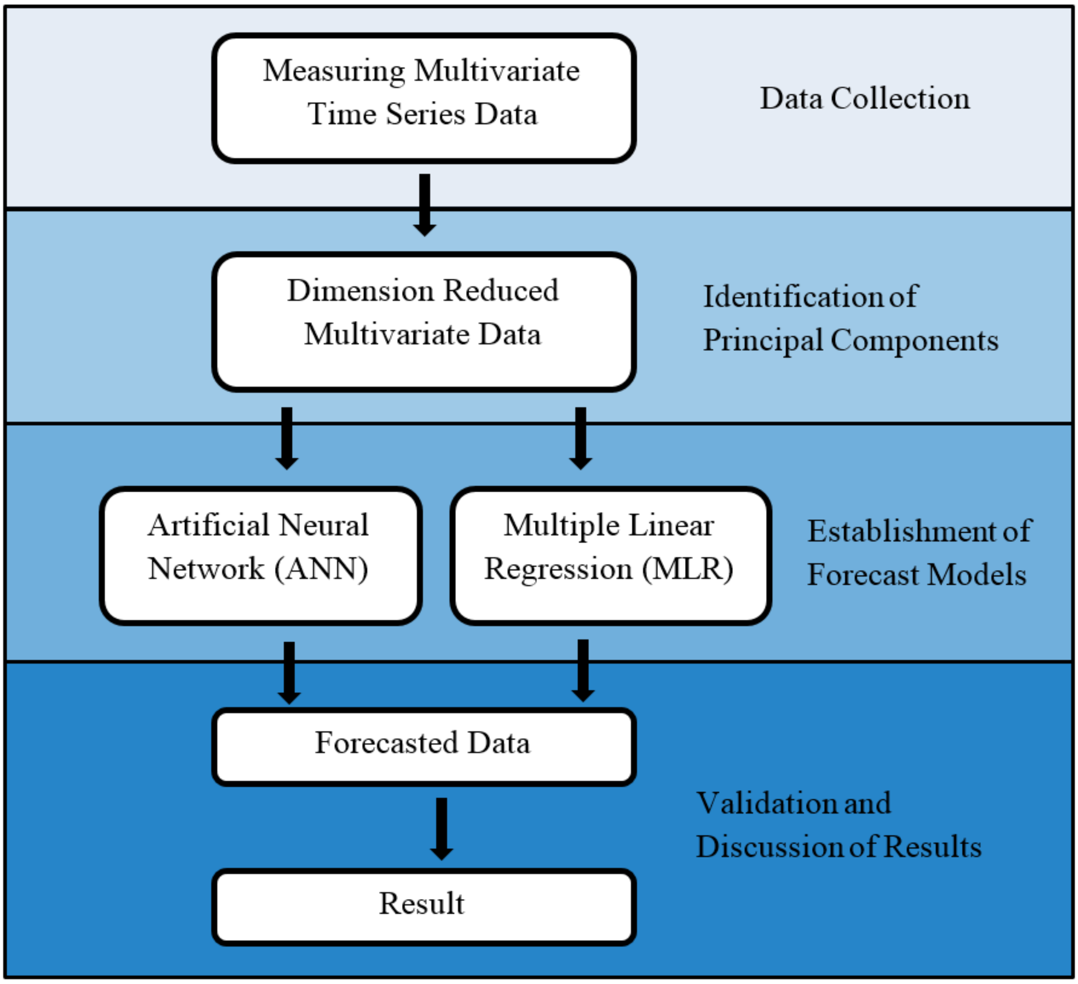
Through these steps, the principal components can be identified. The obtained eigenvalues are then used to determine the percentage of variability accounted and reduce the dimension of the data. In general, an inclusion of variables that accounts a total of 90 % and above variability are considered reasonably good [10].

Subsequently, two prediction models, ANN and statistical models are established based on the dimension reduced data to forecast solar radiation. The accuracy of these two models are then compared using root mean square error (RMSE) to identify which model gives better prediction value. Mathematically, RMSE can be defined as

$$RMSE=\left(\frac{1}{N}\sum_{i-1}^{N}\left(C_i-M_i\right)^2\right)^{\frac{1}{2}} \tag{5}$$

Generally, the methodology can be divided into four phases and can be summarized in Figure 3.1.

Figure 4. Flow of research methodology.



4. Results and Discussions

Based on the correlation analysis between every pairs of variables the following results are obtained (Table 1).

Table 1. Correlation between Input Parameters

	Relative Humidity	Air Temperature	Wind Speed	Wind Direction	Wind Gust
Relative Humidity	1	-0.9514	0.5727	-0.0715	0.6439
Air Temperature	-0.9514	1	-0.5839	0.1052	-0.5908
Wind Speed	0.5727	-0.5839	1	-0.0305	0.6197
Wind Direction	-0.0715	0.1052	-0.0305	1	0.1064
Wind Gust	0.6439	-0.5908	0.6197	0.1064	1

Upon solving the eigenvalues, the percentage of variability accounted by each variables are as follow

Figure 5. Principal components

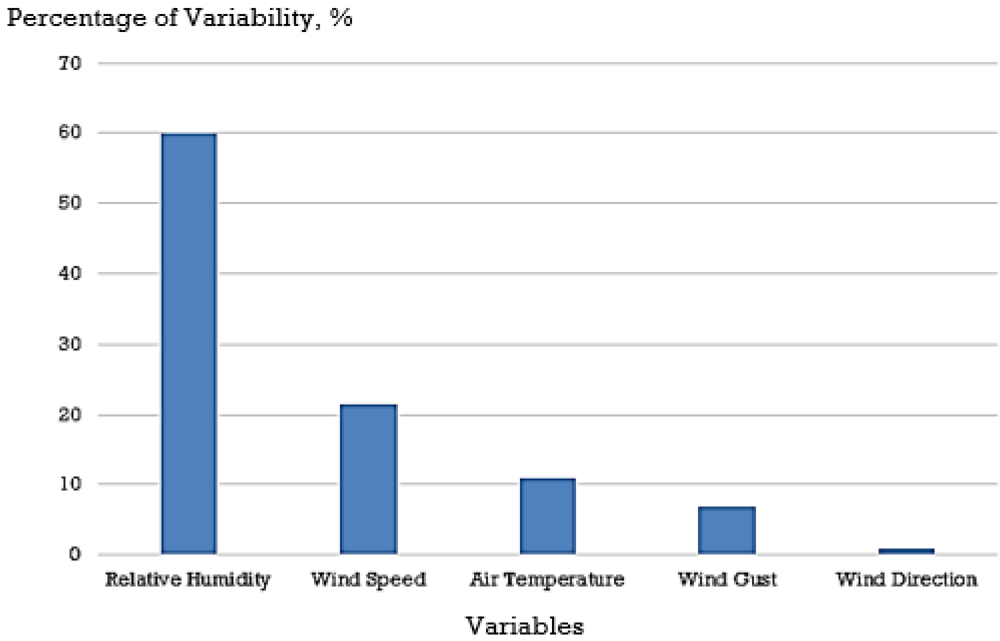


Figure 5 shows the percentage of variability accounted for each variables. Variable with the highest percent of variability accounted is the first principal component. Based on Figure 5, it can be seen that the first three components is relative humidity (59.872 %), wind speed (21.414 %), and air temperature (11.026 %). Furthermore, the total variability accounted by these three variables is 92.312 %. Since these first three principal components have accounted for more than 90 %, the rest of two variables can be regarded as redundant variables. The elimination of these two variables accounts a total loss of only 7.688 % variability.

4.3 Solar Radiation Forecast Models

Based on the PCA results from the previous section, only three variables were used to establish the forecast models. They are relative humidity, wind speed and air temperature. Two different models i.e., ANN and statistical were used to forecast the solar radiation.

4.3.1 Artificial Neural Network

The recommended default setting that were used in training the network is as follow

Table 2. Recommended default setting of ANN

Learning Rate	0.9
Momentum	0.3
Initial Weight	0.3

Using this setting, ANN networks for one variable (relative humidity), two variables (relative humidity and wind speed), and three variables (relative humidity, wind speed and air temperature) were established. Figure 6, Figure 7 and Figure 8 shows the predicted solar radiation results based on three different ANN networks.

Figure 6. Time series plot of predicted solar radiation using first principal component (relative humidity)

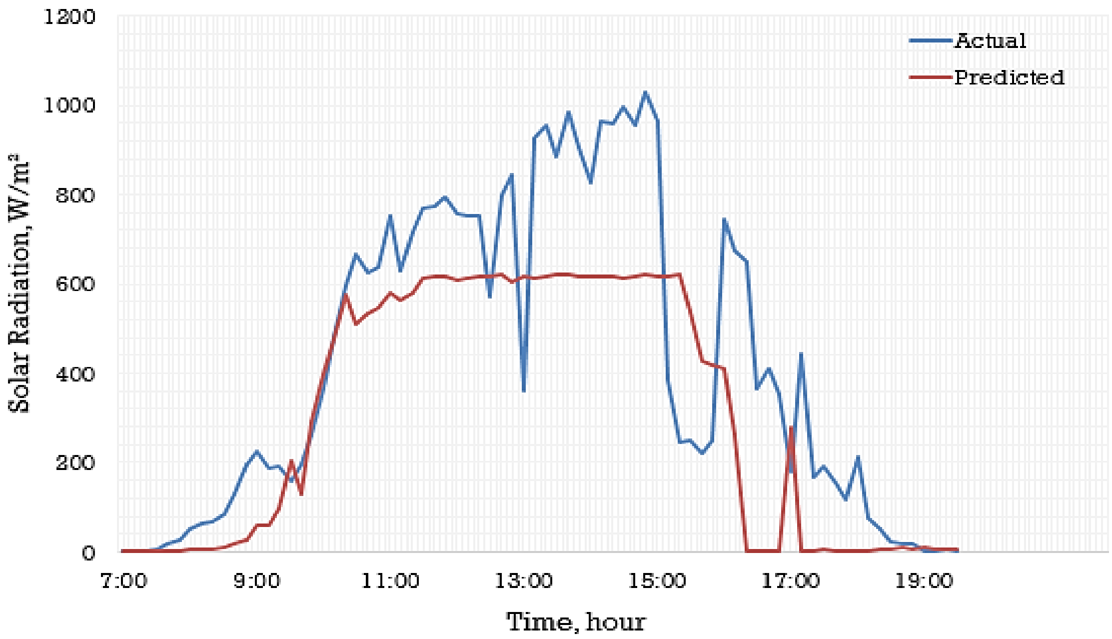


Figure 7. Time series plot of predicted solar radiation using first two principal components (relative humidity and wind speed)

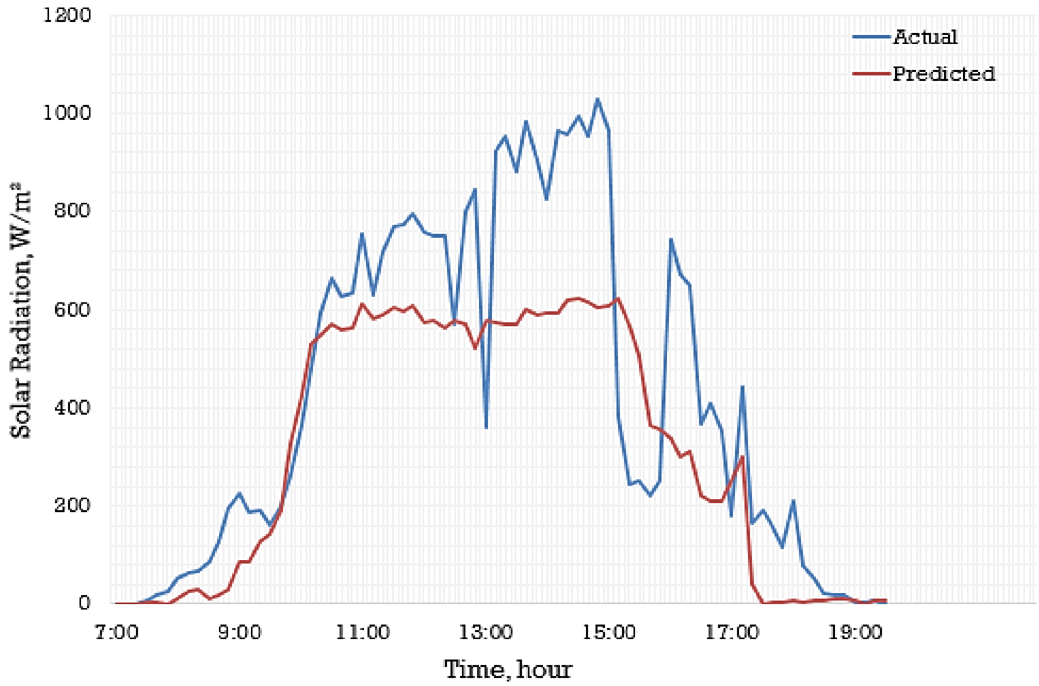
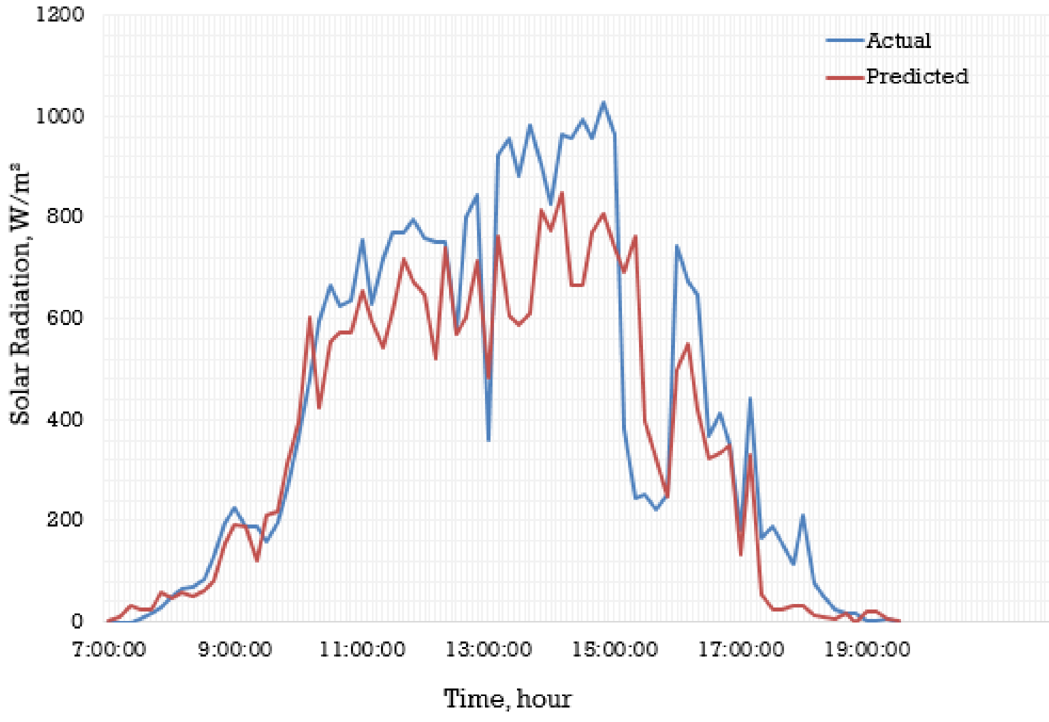


Figure 8. Time series plot of predicted solar radiation using first three principal components (relative humidity, wind speed and air temperature)



By visual inspection, it can be seen that, it can be seen that the predicted curve are able to capture the actual trend reasonably well. Furthermore, the model which uses three variables Figure 8 shows lesser error as compared to Figure 7. The prediction results from Figure 7 also shows better trend as compared to Figure 6. This shows that accounting more variables in solar radiation prediction can significantly improve forecast accuracy. The details of the error analysis are presented in Section 4.4.1.

4.3.2 Multiple Linear Regression (MLR)

Prior to establishing a statistical model, the existence of seasonality pattern were first determined via plotting the lag diagram. The result is presented in Figure 9.

Figure 9. Autocorrelation Function (ACF) of the time series versus lag

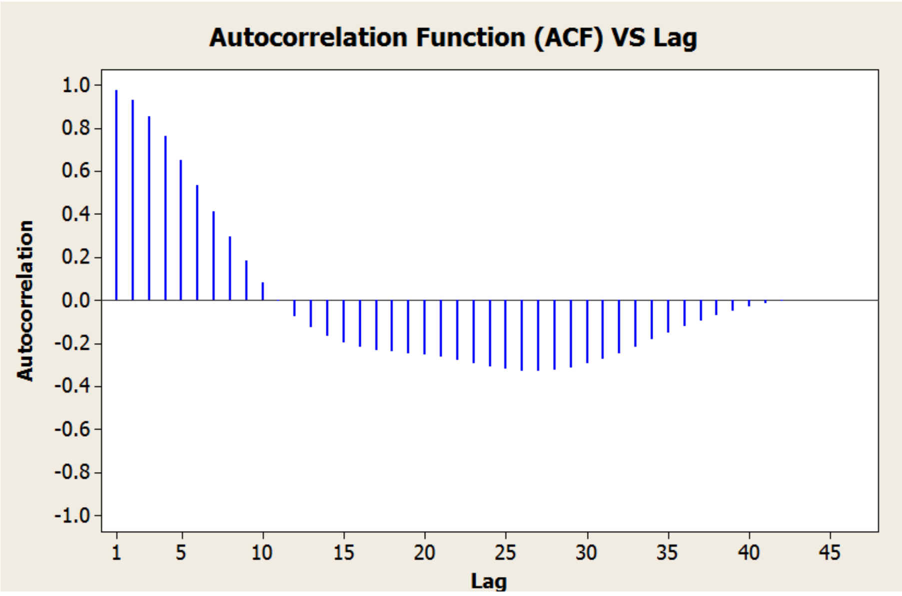


Figure 9 shows the autocorrelation function versus lag. As can be observed, the autocorrelation function (ACF) starts to cut off at lag 2 and dies down extremely slowly with an increased in the lag number. Such trend indicates that the time series data sets is non-seasonal.

Similar to ANN, 3 different forecast models will be established. The first model uses only one variable (relative humidity), the second uses two variables (relative humidity and wind speed), and the third uses three variables (relative humidity, wind speed and air temperature). The predicted solar radiation and actual solar radiation for the three cases were plotted as Figure 10, Figure 11, and Figure 12 respectively.

Figure 10. Predicted solar radiation using first principal component (relative humidity)

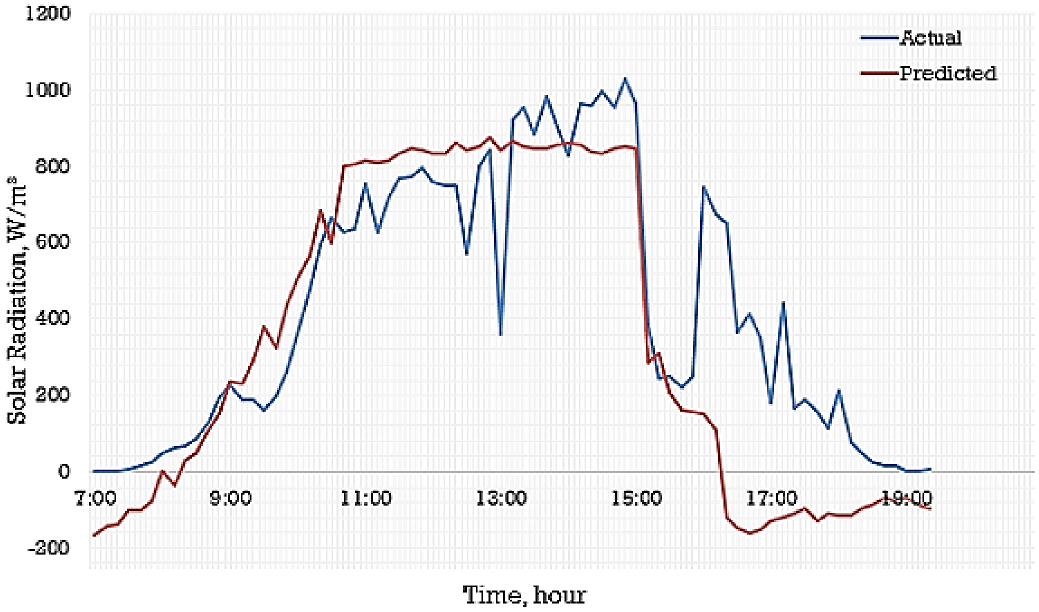


Figure 11. Predicted solar radiation using first two principal components (relative humidity and wind speed)

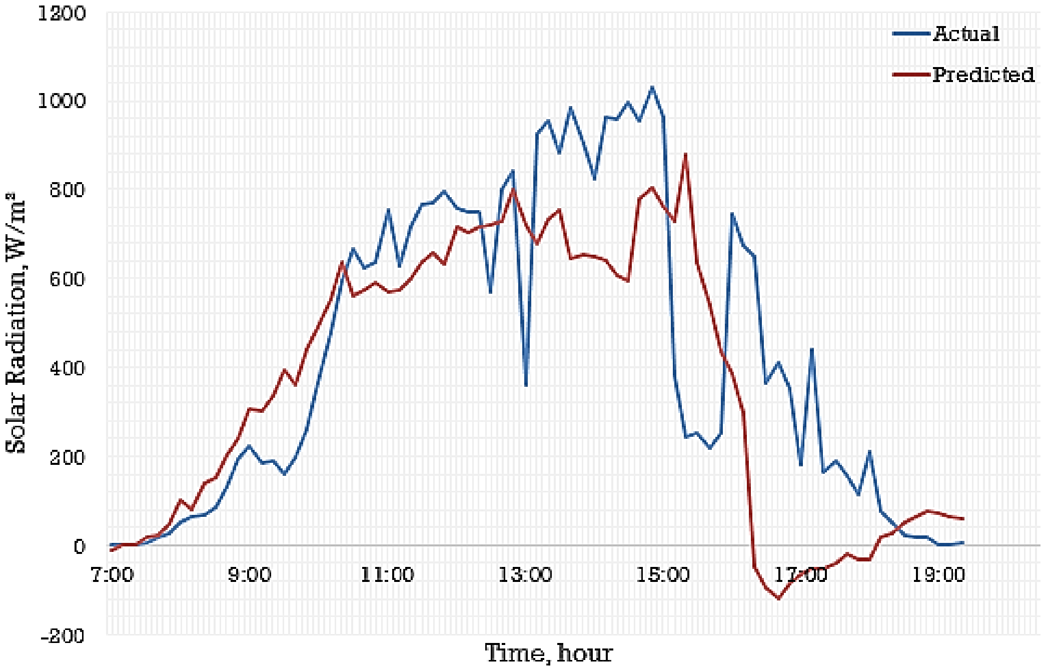
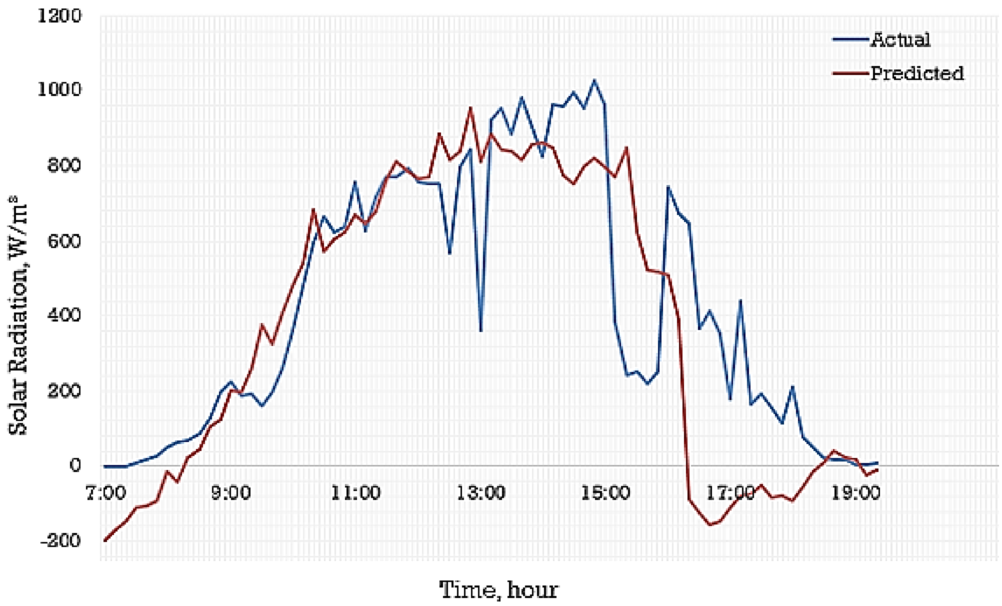


Figure 12. Predicted solar radiation using first three principal components (relative humidity, wind speed and air temperature)



From Figure 11 and Figure 12, it can be seen that the forecasted results in Figure 12 shows fairly accurate prediction results as compared to Figure 11. While, the prediction results from Figure 11 shows a lesser errors as compared to Figure 10. This also shows that including more variables into solar radiation prediction can improve the accuracy of the predicted results. The details of the error analysis are presented in Section 4.4.1.

4.4.1 Root Mean Square Error (RMSE)

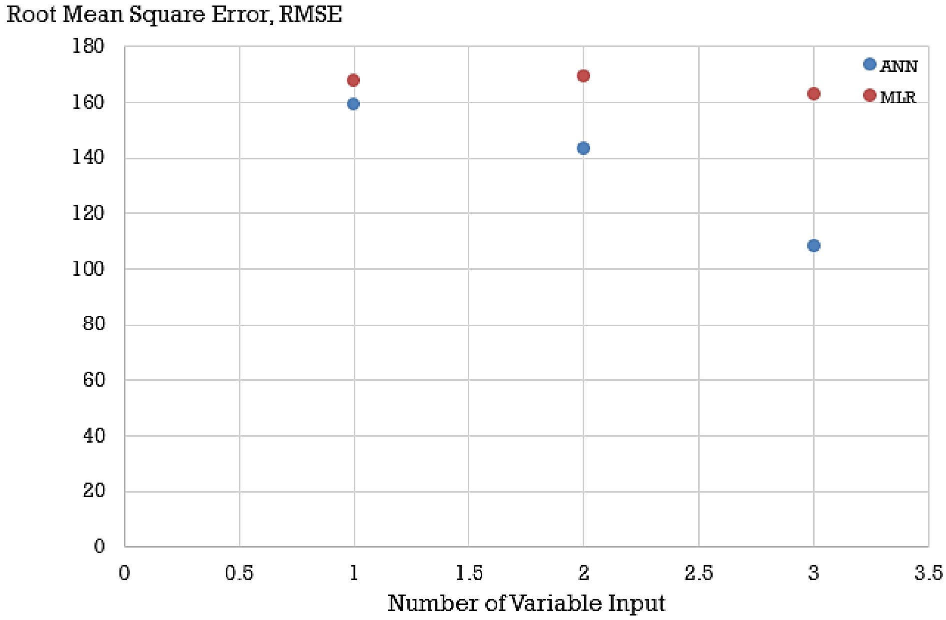
The RMSE on two different solar radiation forecasting models were computed via Equation (10). The obtained RMSE results were tabulated in Table 4.4.

Table 3. Root mean square error between two different forecasting models

Number of Variables Input	RMSE accounted by ANN	RMSE accounted by MLR
1	159.28	164.81
2	143.09	169.20
3	108.35	162.89

Graphically, the obtained RMSE can be displayed as followed.

Figure 13. RMSE accounted by ANN and MLR



It can be seen that ANN generally has better performance as this model accounts for lower RMSE. This shows that ANN model is able to give a better prediction values as compared to MLR.

5. Conclusions

A methodology for forecasting solar radiation based on several meteorological factors has been proposed. In the methodology, the employment of PCA, which is a dimension reduction technique, discards redundant variables to reduce the complexity of the multivariate time series data prior to forecasting. Through the implementation of PCA, it was found that relative humidity, wind speed and air temperature are significant meteorological factors affecting solar radiation. Thus, these three components were retained for the forecasting process. By employing those significant variables into the forecast models (ANN and MLR), solar radiation several minutes in advanced could fairly accurately predicted. Furthermore, this methodology requires lower computational time since it only uses three variables. Based on the RMSE analysis, it can be concluded that ANN generally has a better performance as this model accounts for lower RMSE than MLR. It is expected that better prediction results can be achieved by including more variables or manipulating the parameters (learning rate, momentum, and initial weight, number of data set) in ANN.

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SICASE-0022

"Ohmic Heating" A New Method To Extraction Of Citronella Oil

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Abstract